Do Bank Failures Affect Real Economic Activity? New Evidence from the Pre-Depression Era

Carlos D. Ramirez
Department of Economics
George Mason University
Fairfax, VA 22030-4444
Phone: 703-993-1145
email: cramire2@gmu.edu

Philip A. Shively
Division of Insurance and Research
Federal Deposit Insurance Corporation
550 17th Street, NW, Room 4206
Washington, DC 20429
Phone: 202-898-8545
email: pshively@fdic.gov

Abstract

A central question in monetary economics is: To what extent do bank failures affect real economic activity? This paper examines the existence, source, size, and dynamic effect of a credit channel using newly-constructed, state-level time series of bank failures normalized by bank deposits and commercial failures normalized by state income from 1900Q1 through 1931Q2 for the 48 contiguous states. Consistent with Bernanke (1983), we find significant evidence of a credit channel at the aggregate U.S. level and in 23 of the 48 states, with 5 more states near significance. We find that the cross-sectional variation across states is consistent with the two explanations of a credit channel advanced by Bernanke (1983): a demand-side disruption of funds from the slow liquidation of failed-bank deposits, and the supply-side disruption of credit to bank-dependent firms. We find that branch banking, state-sponsored deposit insurance, and an agricultural-manufacturing split do not explain the cross-sectional variation. Using aggregate U.S. data, our structural model indicates that bank failures account for about 20% of commercial failures at all forecast horizons and have a large impulse response in the first two quarters, and that bank failures have a large but very short-lived impulse response in the banking sector.

1 Introduction

A central question in monetary economics is: To what extent do bank failures affect real economic activity? This question has attracted considerable attention over time because of the importance of financial intermediaries in the economy. The seminal book of Friedman and Schwartz (1963) was the first empirical work to establish a relationship between bank failures and real economic activity. Using the Great Depression as an example, they found that the banking collapse of the period caused a contraction in the money multiplier, which converted what may have been a recession into a deep and protracted depression. Twenty years later, Bernanke (1983) offered another interpretation of the Depression in which he linked financial disintermediation to economic distress through a "credit" channel. He argued that bank failures affect real economic activity because the resulting contraction in bank credit deprives bank-dependent customers of funds precisely when their balance sheets are weakest and they need funds the most.

The contribution of Bernanke (1983), which was motivated by contemporaneous advances in the economics of information, gave rise to an important debate regarding the extent to which there is a credit channel linking financial disintermediation and real economic performance. In recent work, Calomiris and Mason (2003) and Anari, Kolari, and Mason (2004) find evidence of a credit channel in Depression era data. Calomiris and Mason (2003) use county level data from 1930 through 1932 to identify loan-supply shocks and find that a one-standard-deviation decrease in loan-supply growth results in a substantial decline of 7% to 9% in local income over their two-year sample period. Anari, Kolari, and Mason (2004) extend Bernanke's (1983) work by explicitly testing the role of deposit liquidation in explaining the persistence of the Great Depression. Using a vector autoregression model, they find that the stock of deposits in failed banks is as important as the money stock in explaining output changes during the Depression.

One drawback of this research is that it focuses on the banking experience of the Depression era. This period was unique in U.S. economic history, however, in that the banking industry and the economy both contracted on an unprecedented scale. Given the magnitude and persistence of the Depression, it is not surprising that these studies find evidence linking financial disintermediation to economic distress, whether through the credit channel or any other channel. Consequently, it is important to examine other time periods before and after the Depression to determine the extent to which these results may be generalized.

Research using post-Depression era data has not yielded a concensus regarding the relationship between bank failures and real economic activity. Ashcraft (2003) examines FDIC-induced closures of 38 subsidiaries of First RepublicBank Corporation in 1988 and 18 subsidiaries of First City Bank Corporation in 1992 to determine the extent to which bank closures affect local economic conditions. He found that real income declines by about 3% at the county level. Alternatively, Gilbert and Kochin (1989) and Clair and O'Driscoll (1994) do not find such a link. Gilbert and Kochin (1989) use county level data from Kansas, Nebraska and Oklahoma between 1981 and 1986 and find that bank failures do not have any significant affect on local economic activity, as measured by sales and employment. Clair and O'Driscoll (1994) follow Gilbert and Kochin's (1989) methodology and examine the impact of bank failures on local economic activity in several Texas counties between 1981 and 1991. Like Gilbert and Kochin (1989), they were unable to find a significant relationship between bank failures and local economic conditions.

One limitation of using post-Depression era data is that the number of bank failures in this period has been very small, with the exception of the late 1980s and early 1990s. Consequently, research into the credit channel using data after the Depression most likely is driven by the economic experience of this brief, and perhaps unique, period. The alternative is to evaluate the credit channel using pre-

Depression era data. The pre-Depression era offers a natural experiment before the financial reforms of the New Deal when there were many bank failures over a variety of economic periods. The problem with evaluating the pre-Depression era is that the appropriate data are very difficult to obtain.

To our knowledge, Grossman (1993) is the only study to address the credit channel using data prior to the Depression. Using monthly U.S. bank failures from the national banking era of 1865 through 1914, he found that small-bank failures can lead to a 2% decline real economic activity and large-bank failures can lead to as much as a 20% decline. The purpose of this paper is to determine the existence, source, size and dynamic effect of a credit channel using pre-Depression era data. We constructed two new state-level, quarterly time series of bank failures normalized by bank deposits and commercial failures normalized by state income from the first quarter of 1900 through the second quarter of 1931 for the 48 contiguous United states. These data include over 24,000 hand-collected liabilities of bank failures, manufacturing failures, trade failures, and other failures from Dun's *Review*.

Consistent with Bernanke's (1983) finding of a credit channel, we find statistically-significant evidence of a credit channel at the aggregate U.S. level and in 23 of the 48 contiguous states, with 5 more states near significance. By collecting data at the state level, we are able to use the cross-sectional variation in the evidence of a credit channel across states to evaluate propagation theories of bank failures and sources of the credit channel. We find that the cross-sectional variation is consistent with the two explanations of a credit channel advanced by Bernanke (1983), as well as Calomiris and Mason (2003) and Anari, Kolari, and Mason (2004): a demand-side disruption of funds from the slow liquidation of failed-bank deposits, and the supply-side disruption of credit to bank-dependent firms. Alternatively, we find that branch banking, state-sponsored deposit insurance, and an agricultural-manufacturing split do not explain the cross-sectional variation in the evidence of a credit channel across states. We use

4

a structural moving-average model with aggregate U.S. data to evaluate the size and dynamic effect of the credit channel. We find that bank failures account for about 20% of commercial failures at all forecast horizons, and they have a large impulse response in the first two quarters. We also find that bank failures have a large but very short-lived impulse response in the banking sector, which implies that they are well-managed.

The remainder of this paper is organized as follows: Section 2 describes the data, Section 3 tests for the existence of a credit channel, Section 4 investigates explanations of the credit channel, Section 5 determines the size and dynamic effect of bank failures and commercial failures, and Section 6 concludes.

2 Data

The data are quarterly liabilities of bank failures, manufacturing failures, trade failures, and other failures by state for the 48 contiguous United States from the first quarter of 1900 through the second quarter of 1931. These data are over 24,000 hand-collected observations from Dun's *Review*.[1] There were many errors in the original data, such as misaligned data, typographical errors, additions, etc., which we found using a variety of checking procedures. We carefully "cleaned" the original data and then constructed two time series: bank failures normalized by total state bank deposits and commercial failures normalized by state income. We normalize the two series for comparability across states.

Total bank deposits are available by state on an annual basis from *All Bank Statistics*, as reported by Flood (1998), which we linearly interpolated to obtain quarterly

---

[1]Dun's *Review* does not clarify whether bank suspensions are included in bank failures. To get an idea of whether suspensions were included with bank failures, we compared our *number* of aggregate U.S. bank failures with the total number reported by Goldenweiser (1932, Table I). We find that our number is marginally higher than Goldenweiser's before 1920, but substantially smaller thereafter. This can be explained by the fact that Goldenweiser (1932) did not include suspensions prior to 1921 (at least for national banks), which empirically supports our contention that our bank failures include few, if any, suspensions.

estimates. Commercial failures are the sum of manufacturing failures, trade failures, and other failures. State income is not available periodically prior to 1929. However, it is available annually from 1929 onward from the Bureau of Economic Analysis (1989). Consequently, we impute state income using a money-demand equation

$$\frac{M}{PY} = \phi(i) \tag{1}$$

where M is money, P is the price level, Y is income, and i is the opportunity cost of capital. Following Ball's (2002) methodology, which emphasizes the estimation of short-run parameters, we estimated the money-demand function annually from 1929 through 1955. Our proxy for money at the state level is total bank deposits and our proxy for the opportunity cost of capital is interest expense divided by total deposits of national banks, which are available from Flood (1998). Prices are not available at the state level. Consequently, we use the wholesale price index Series E23 from the Historical Statistics of the United States because it was the most complete.

We are not able to estimate our money-demand equation reliably for each state because the data span a relatively short period. Instead, we estimate one money-demand equation for the entire U.S. and control for fixed effects across states.[2] Then we impute income annually for each state from 1900 through 1928, accounting for the state-level fixed effects, and interpolate linearly to obtain quarterly values.[3]

Our time period is limited to 1900 through 1931 by the original data in Dun's *Review*. They did not publish consistent failure data by state until the late 1890s, and they stopped publishing failure data after the second quarter of 1931. Consequently, we are not able to replicate results from studies which use depression and post-

---

[2]This approach implicitly assumes that the income and interest elasticity of money demand are the same across states. However, using data from 1965 through 1998, Driscoll (2004) cannot reject the hypothesis that money-demand functions are the same across states. Although he studied another time period, his results provide support for our assumption that the income and interest elasticity of money demand are the same across states.

[3]This procedure for estimating state income should be adequate as long as money demand remained stable during the estimation period. Given that the literature has emphasized the instability of money demand only after the 1970s (Goldfeld, 1973), money demand instability most likely was not an issue in the first half of the 20th century.

depression era data. However, our pre-depression era data is rich enough to capture several well-known periods of financial distress in the early 20th century such as the Banking Panic of 1907.

Figure I presents commercial failures normalized by income and bank failures normalized by bank deposits at the aggregate U.S. level, with both series expressed as percents. Commercial failures at the aggregate U.S. level are fairly consistent across the sample period with a mean of 0.036% and a standard deviation of 0.013%. Bank failures, alternatively, are much more volatile. The mean and standard deviation are 0.084% and 0.173%, respectively, there are large spikes during the banking crises in the fourth quarters of 1907 and 1930, and there is a heightened level of bank failures during the 1920s.

Tables I and II list summary statistics by state, including the minimum, maximum, mean, median and standard deviation, for commercial failures normalized by state income and bank failures normalized by bank deposits respectively, with both series expressed as percents. The tables reveal several interesting features of the state-level data. First, there is considerable cross-sectional variation of commercial failures and bank failures across states. Second, bank failures tend to be much more volatile than commercial failures with a maximum that is 9.7 times larger on average, a mean that is 1.6 times larger, and a standard deviation that is 6.9 times larger. Third, the median value of bank failures is zero in 38 of the 48 states, which shows that many bank-failure observations are zero. Fourth, the mean and median values of bank failures differ considerably in each state, which indicates that the within-state variation of bank failures is due to extreme observations over time. The mean and median values of commercial failures, alternatively, are relatively close.

3   The Existence of a Credit Channel

This section uses an F test for Granger causality to evaluate the relationship between bank failures and commercial failures, which allows us to draw conclusions about the existence of a credit channel. Evidence that bank failures Granger cause commercial failures is evidence in favor of a credit channel. We find statistically-significant evidence that bank failures Granger cause commercial failures at the aggregate U.S. level and in 23 of the 48 states, with 5 more states near significance. In contrast, we do not find evidence that commercial failures Granger cause bank failures.

Let c_t be commercial failures normalized by income at time t, and b_t be bank failures normalized by bank deposits. Then the model used to determine whether bank failures Granger cause commercial failures is

$$c_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i c_{t-i} + \sum_{i=1}^{p} \beta_i b_{t-i} + \epsilon_t \tag{2}$$

and the model used to determine whether commercial failures Granger cause bank failures is

$$b_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i b_{t-i} + \sum_{i=1}^{p} \beta_i c_{t-i} + \epsilon_t. \tag{3}$$

This section uses an F(p, n-2p-1) test of the restricted ($\beta_1 = \cdots = \beta_p = 0$) versus unrestricted model. When we reject the restricted model in favor of the unrestricted model, then we have Granger causality.

Table III lists test statistics and p-values from the F test for Granger causality at the aggregate U.S. level and by state. The model is estimated with $p = 4$ lags, which captures annual variation in quarterly data, and it is estimated with robust standard errors using White's correction. The test finds highly-significant evidence that bank failures Granger cause commercial failures at the aggregate U.S. level with a p-value of 0.000. At the state level, the test finds significant evidence that bank failures Granger cause commercial failures in 23 (18) of the 48 states at the 0.10 (0.05) level, and another 5 states show weaker evidence of Granger causality with p-values

from 0.109 to 0.156. In contrast, the test finds no evidence that commercial failures Granger cause bank failures at the aggregate U.S. level with a p-value of 0.479, and only 2 (0) states show significant evidence that commercial failures Granger cause bank failures at the 0.10 (0.05) level.[4]

The evidence in favor of a credit channel in nearly half of the 48 states is strong enough to show up as a highly-significant credit channel in aggregate economic activity. Furthermore, the evidence that bank failures Granger cause commercial failures in 23 (18) of the 48 states at the 0.10 (0.05) level is much stronger than expected if in fact there were no credit channel. If there were no credit channel, then a type I error would generate only 4.8 (2.4) states with a significant credit channel at the 0.10 (0.05) level. Alternatively, the evidence that commercial failures Granger cause bank failures in only 2 (0) states at the 0.10 (0.05) level is within the margin of a type I error. Consequently, we do not find evidence of a channel from commercial failures to bank failures.

4   Explanations of the Credit Channel

Recent research has advanced two theories to explain the existence of a credit channel: a demand-side explanation in which there is a slow liquidation of failed-bank deposits to consumers, and a supply-side explanation in which there is a disruption of credit to bank-dependent firms. The intuition behind the demand-side explanation is straightforward. According to Bernanke (1983) and Anari, Kolari, and Mason (2004), bank failures reduce aggregate demand through consumption because deposits at failed banks are illiquid assets until the failed banks are liquidated. The supply-side explanation is the essence of the traditional credit-channel literature advanced

---

[4]We do not adjust the data for seasonality. However, we tested whether seasonality affects our results by including seasonal dummies in the regression equations. With seasonal dummies, the F test finds that bank failures Granger cause commercial failures in 24 states at the 0.10 level whereas commercial failures do not Granger cause bank failures in any state at the 0.10 level. Consequently, our results change only marginally and in a direction that is more favorable to the credit channel.

by Bernanke (1983) and Calomiris and Mason (2003). In a world where finanical markets are incomplete, a disruption in financial intermediation increases the cost of borrowing for information-intensive borrowers, which effectively tightens credit and reduces aggregate supply. DeLong (1992), Carrosso (1970) and Lamoreaux (1988) argue that this explanation is particularly important in the pre-Depression era when financial markets were much less sophisticated and long-lasting banking relationships were common for medium and large firms, as well as smaller bank-dependent firms.

We exploit the cross-sectional variation in the evidence of a credit channel across states in order to determine whether it is consistent with the demand-side or supply-side explanations of the credit channel. Our measure of a demand-side disruption of funds to consumers is per capita bank deposits in 1896, which is total bank deposits normalized by population. Our measure of a supply-side disruption of credit to bank-dependent firms is per capita net bank loans in 1896, which is total bank loans less real estate loans normalized by population. These data are obtained at the state level from *All Bank Statistics*, and reported by Flood (1998). We use data from 1896 in order to avoid endogeneity problems with our sample period, we normalize by state population for comparison across states, and we subtract real estate loans from total bank loans in order to isolate bank loans to the commercial sector.

In order to test the demand-side explanation of the credit channel, we partition states by the median per capita bank deposit and refer to the 24 states above (below) the median as high (low) bank deposit states.[5] The idea behind this partition is that high (low) bank deposit states are more (less) likely to have an operative credit channel if the demand-side explanation is true. We find that the high bank deposit states aggregated together have a p-value of 0.000, which is highly consistent with an operative credit channel, and we find that 16 of the 23 states (70%) that have

---

[5]The 24 high bank deposit states are California, Colorado, Connecticut, Delaware, Illinois, Iowa, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Montana, Nebraska, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Utah, Vermont, Wisconsin, and Wyoming.

a credit channel are high bank deposit states. Alternatively, the low bank deposit states aggregated together have a p-value of 0.208, which is not consistent with an operative credit channel, and only 7 of the 23 states (30%) with a credit channel are low bank deposit states.

In order to test the supply-side explanation of the credit channel, we partition states by the median per capita net bank loan and refer to the 24 states above (below) the median as high (low) bank loan states.[6] This partition is useful because high (low) bank loan states are more (less) likely to have an operative credit channel if the supply-side explanation is true. We find that the high bank loan states aggregated together have a p-value of 0.000, which is highly consistent with the credit channel, and 17 of the 23 states (74%) that have a credit channel are high bank loan states. In contrast, the low bank loan states aggregated together have a p-value of 0.260, which is not consistent with an operative credit channel, and only 6 of the 23 states (26%) with a credit channel are low bank loan states.[7]

We find that the cross-sectional variation in the evidence of a credit channel across states is consistent with both the demand-side and supply-side explanations of a credit channel. A natural extension is to determine whether other state-level regulatory or structural characteristics help to explain the likelihood of having an operative credit channel. Previous research indicates that branch-banking regulations, state-sponsored deposit insurance, and an agricultural-manufacturing partition of states may be important factors.[8] In order to evaluate whether these factors influence the

---

[6]The 24 high bank loan states are California, Colorado, Connecticut, Delaware, Illinois, Iowa, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Montana, Nebraska, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Vermont, Wisconsin, and Wyoming.

[7]Miron, Romer and Weil (1997) evaluate the credit channel at the aggregate U.S. level using a similar measure of bank-dependent financing. They subtract real estate loans from total bank loans in order to isolate bank loans to the commercial sector, but they normalize by total interest bearing bank assets instead of population. We evaluated their measure of financial depth and found that it does not explain the aggregate or state-level evidence of a credit channel.

[8]White (19xx), Calomiris (2000), Mitchener (2004), and Ramirez (2003) find evidence that branch banking influences bank failures; Wheelock (19xx), Calomiris (2000), and White (1997) find that state-sponsored deposit insurance increases the likelihood of bank failures; and Calomiris (1992) and

likelihood of having an operative credit channel, we fit a logit regression in which the dependent variable is 1 for the 23 states that show evidence of a credit channel at the 0.10 level in Table III, and 0 for the remaining 25 states. The independent variables are a branch-banking indicator,[9] a deposit-insurance indicator,[10] and an agricultural-state indicator,[11] which are set to 1 if the state possesses the characteristic and 0 otherwise. Consequently, these logit regressions evaluate the significance of the relationship between the characteristic and the credit channel.

The logit regression results are presented in Table IV. They show that none of these state-level regulatory or structural characteristics, individually, is significant in explaining an operative credit channel.[12] We contrast these results with those obtained from similar logit regressions setting the independent variable to 1 for the 24 high bank deposit states and the 24 high net loan states, and 0 otherwise. Table IV confirms that both factors, individually, are highly significant indicators of an operative credit channel. Furthermore, the coefficient of the high net loan indicator is larger and slightly more significant than the coefficient of high bank deposit indicator, which suggests that high net loans (aggregate supply) is a better predictor of an operative credit channel than high bank deposits (aggregate demand). This is consistent with the results above where we find that 17 of the 23 states (74%) consistent with an operative credit channel are high bank loan states whereas 16 (70%) are high bank

Alston, et al (1994) find that bank failures were higher in highly agricultural states.

[9]Branch-banking states are from White's (1983) Table 4. There are 10 states with state-wide branching: Arizona, California, Delaware, Georgia, Maryland, North Carolina, Rhode Island, South Carolina, Tennessee, and Virginia; and 9 states with limited branch banking: Louisiana, Maine, Massachusetts, New York, Ohio, Mississippi, Pennsylvania, Kentucky, and Michigan.

[10]States with deposit insurance are from the FDIC Annual Report of 1955: Kansas (1909-1929), Mississippi (1914-1930), Nebraska (1911-1930), North Dakota (1917-1929), Oklahoma (1908-1923), South Dakota (1916-1927), Texas (1910-1927), and Washington (1917-1921).

[11]Agricultural states are from Calomiris and Ramirez (19xx). They are state for which at least 55% of state income is from agriculture: Alabama, Arkansas, Georgia, Idaho, Indiana, Iowa, Kansas, Minnesota, Mississippi, Montana, Nebraska, New Mexico, North Carolina, Oklahoma, Oregon, South Carolina, South Dakota, Tennessee, Texas, Vermont, Wisconsin, and Wyoming.

[12]Deposit insurance was not in effect over the full sample period for any of the 8 states with deposit insurance. However, if a state with deposit insurance had (did not have) an operative credit channel over the entire sample period, then it also had (did not have) an operative credit channel over the subperiod during which the state had deposit insurance.

deposit states.

5 The Size and Dynamic Effect of Bank and Commercial Failures

This section presents forecast-error variance decompositions and impulse response functions from a structural moving-average model in order to show the size and dynamic effect of bank failures and commercial failures at the aggregate U.S. level. There are two main findings. First, regarding the credit channel, we find that bank failures account for approximately 20% of commercial failures across all forecast horizons, and they have a large impulse response in the first two quarters. Second, bank failures have a large but very short-lived impulse response in the banking sector, which implies that they are well-managed.

Let $x_t = (c_t, b_t)'$ where c_t and b_t are defined above, then the vector autoregression (VAR) under consideration is

$$x_t = \delta + \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t \tag{4}$$

where δ is a (2 x 1) vector of constants, p is the number of VAR lags, ϕ_i is a (2 x 2) parameter matrix, and ϵ_t is a mean zero vector of innovations with covariance structure Σ. Equation (4) can be rewritten as

$$\Phi(L)x_t = \epsilon_t \tag{5}$$

and inverted to an infinite-order moving-average model

$$x_t = C(L)\epsilon_t \tag{6}$$

where $C(L) = \Phi(L)^{-1}$ and the contemporaneous effect of ϵ_t on x_t is the identity matrix. Equation (6) is a reduced-form model since the innovations ϵ are contemporaneously correlated with covariance structure Σ. We need a structural model with

orthogonal innovations in order to draw inference about the size and dynamic effect of bank failures and commercial failures.

Our structural model is

$$x_t = A(L)\eta_t \tag{7}$$

where η_t is a mean zero vector of orthogonal innovations with a covariance structure normalized to the identity matrix. We identify the structural model by comparing Equations (6) and (7) and observing that $\epsilon_t = A(0)\eta_t$ and $A(k) = C(k)A(0)$, where $A(0)$ is the contemporaneous effect of η_t on x_t. Therefore the four elements of $A(0)$ just identify the structural model. We use two types of restrictions to identify the structural model: covariance restrictions and a contemporaneous restriction on one of the two structural innovations. Covariance restrictions establish three of the four restrictions necessary to identify $A(0)$, since $\Sigma = A(0)A(0)'$. The fourth restriction is an assumption that the contemporaneous response of bank failures to commercial failures is zero.

We estimate the structural model at the aggregate U.S. level where we find that bank failures Granger cause commercial failures and commercial failures do not Granger cause bank failures. Consequently, we impose this triangular restriction on the reduced-form matrices $C(k)$. In conjunction with the contemporaneous triangular restriction on the matrix $A(0)$, the structural matrices $A(k) = C(k)A(0)$ are also triangular and the credit channel flows through from the reduced-form VAR to the structural model.[13]

Table V presents forecast-error variance decompositions and Figure II presents impulse response functions from the structural model at the aggregate U.S. level. The structural model is estimated with 4 VAR lags, a choice which captures annual variation in quarterly data and is supported by a likelihood ratio test which finds that

---

[13]We estimated the structural model without imposing the triangular, credit-channel restriction on the reduced-form matrices $C(k)$ and find that the results change very little. The forecast-error variance decompositions from the unrestricted model are within 1.5 percentage points of the restricted model at all forecast horizons, and the impulse response functions are nearly identical.

the reduced-form VAR residuals are consistent with white noise. The forecast-error variance decompositions are normalized such that the variances of the two structural innovations sum to 100%. The forecast-error variance decompositions and impulse response functions are presented with one-standard-error confidence intervals, which are bootstrapped using 1,000 repetitions of the model.

There are four combinations of bank failures and commercial failures to consider. First, and most importantly, is the credit channel in which bank failures Granger cause commercial failures. The forecast-error variance decompositions in Table V show that bank failures account for approximately 20% of commercial failures across all forecast horizons, with a small hump at short-run and medium-run horizons. The impulse response functions in Figure II show that bank failures have a relatively large impact on commercial failures in the first two quarters, but fall quickly and then diminish slowly over time. Second, bank failures account for 100% of bank failures at all forecast horizons, by construction, and the impulse response is large but very short lived. Third, commercial failures do not have any impact on bank failures by construction. And fourth, commercial failures account for approximately 80% of commercial failures across all forecast horizons, with a small dip at short-run and medium-run horizons, and their impulse response diminishes fairly consistently over time.

6 Conclusion

This paper evaluates the existence, source, size, and dynamic effect of a credit channel in which bank failures affect real economic activity. This issue has attracted considerable attention over time because of the importance of financial intermediaries in the economy. However, previous studies have used either depression era data, which is an atypical economic period, or post-depression era data, which is driven by the brief, and perhaps unique, economic experience of the late 1980s and early 1990s. This

15

paper evaluates the credit channel using pre-Depression era data, a period before the New Deal financial reforms in which there were many bank failures over a variety of economic periods. We constructed two new state-level, quarterly time series of bank failures normalized by bank deposits and commercial failures normalized by state income from the first quarter of 1900 through the second quarter of 1931 for the 48 contiguous United states. These data include over 24,000 hand-collected liabilities of bank failures, manufacturing failures, trade failures, and other failures from Dun's *Review*.

Consistent with Bernanke's (1983) finding of a credit channel, we find statistically-significant evidence of a credit channel at the aggregate U.S. level and in 23 of the 48 states, with 5 more states near significance. We find that the cross-sectional variation in the evidence of a credit channel across states is consistent with the two explanations of a credit channel advanced by Bernanke (1983), as well as Calomiris and Mason (2003) and Anari, Kolari, and Mason (2004): a demand-side disruption of funds from the slow liquidation of failed-bank deposits, and the supply-side disruption of credit to bank-dependent firms. In contrast, we find that branch banking, state-sponsored deposit insurance, and an agricultural-manufacturing split do not explain the cross-sectional variation in the evidence of a credit channel across states. Using a structural moving-average model with aggregate U.S. data, we find that bank failures account for about 20% of commercial failures at all forecast horizons, and they have a large impulse response in the first two quarters. We also find that bank failures have a large but very short-lived impulse response in the banking sector, which implies that they are well-managed.

16

References

Alston, Lee J., Wayne A. Grove, and David C. Wheelock (1994). "Why Do Banks Fail? Evidence From the 1920s," *Explorations in Economic History* Volume 31, pp. 409-31.

Anari, Ali, James Kolari, and Joseph Mason. (2004) Bank Asset Liquidation and the Propagation of the U.S. Great Depression. *Journal of Money, Credit and Banking*, forthcoming.

Ashcraft, Adam B. (2003) "Are Banks Really Special? New Evidence from the FDIC-induced Failure of Healthy Banks," manuscript, Federal Reserve Bank of New York.

Ball, Laurence. (2002). "Short Run Money Demand." Manuscript. Johns Hopkins University.

Bernanke, Ben S. (1983) "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression," *American Economic Review* Volume 73, Issue 3, pp. 257-276.

Calomiris, Charles W. (1992). "Do Vulnerable Economies Need Deposit Insurance? Lessons from U.S. Agriculture in the 1920s," pp. 237-314. In Philip L. Brock (ed.) If Texas Were Chile: A Premier on Banking Reform. Institute for Contemporary Studies Press, San Francisco, CA.

Calomiris, Charles W. (1993). "Financial Factors in the Great Depression," *Journal of Economic Perspectives*, Volume 7, No. 2, pp. 61-85.

Calomiris, Charles W. (1993). "Regulation, Industrial Structure, and Instability in U.S. Banking: An Historical Perspective," pp. 19-116. In M. Klausner and L.J. White (eds.) Structural Change in Banking. Business One Irwin, Homewood, IL

Calomiris, Charles W. and Joseph Mason. (2003) Consequences of Bank Distress During the Great Depression. *American Economic Review*, Volume 93, Issue 3, pp. 937-947.

Clair, Robert T. and O'Driscoll, Gerald P. (1994). "Is Banking Different? A Reexamination of the Case for Regulation," *CATO Journal*, Winter, Volume 13, Issue 3, pp. 345-353.

Friedman, Milton and Anna J. Schwartz. (1963). A Monetary History of the United States, 1867 - 1960. Princeton, NJ: Princeton University Press

Gilbert, Alton and Levis Kochin. (1989) "Local Economic Effects of Bank Failures," *Journal of Financial Services Research*, Volume 3, pp. 333-345.

Goldfeld, Stephen M. (1973). "The Demand for Money Revisited," *Brookings Papers on Economic Activity*, 3, pp. 577-638.

Grossman, Richard. (1993) "The Macroeconomic Consequences of Bank Failures Under the National Banking System," *Explorations in Economic History* 30

(3), July 1993, pp. 294-320.

Hamilton, James D. (1995) Time Series Analysis. Princeton University Press, Princeton, NJ.

Haubrich, J.G. (1990). "Non-monetary Effects of Financial Crises: Lessons from the Great Depression in Canada," *Journal of Monetary Economics* 25, pp. 223-252.

Mitchener, Kris J. (2004). "Bank Supervision, Regulation, and Financial Instability During the Great Depression," National Bureau of Economic Research Working Paper 10475.

U.S. Bureau of the Census. Historical Statistics of the United States, Colonial Times to 1970. U.S. Government Printing Office, Washington D.C.

Wheelock, David C. (1992). "Regulation and Bank Failures: New Evidence from the Agricultural Collapse of the 1920s," *Journal of Economic History* 52, pp. 806-825.

Wheelock, David C. (1993). "Government Policy and Banking Market Structure in the 1920s," *Journal of Economic History* 53, pp. 857-79.

Wheelock, David C. and Paul W. Wilson (1994). "Can Deposit Insurance Increase the Risk of Bank Failure? Some Historical Evidence," *Economic Review*, Federal Reserve Bank of St. Louis, May/June, pp. 57-71.

White, Eugene N. (1982). "The Political Economy of Banking Regulation, 1864-1933," *Journal of Economic History* 42, pp. 33-40.

White, Eugene N. (1983). Regulation and Reform of the American Banking System, 1900-1929. Princeton University Press, Princeton, NJ.

White, Eugene N. (1984). "A Reinterpretation of the Banking Crisis of 1930," *Journal of Economic History* 44, pp. 119-138.

White, Halbert (1980). "A Heteroskedasticity-consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica* 48, pp. 817-838.

Table I
Summary Statistics:
Commercial Failures as a Percent of State Income
Quarterly Data by State from 1900Q1 through 1931Q2

State	Minimum	Maximum	Mean	Median	Std Dev
Alabama	0.0004	1.0765	0.1005	0.0612	0.1430
Arizona	0.0000	4.6226	0.2385	0.1382	0.4689
Arkansas	0.0095	0.8809	0.1414	0.1110	0.1229
California	0.0055	0.1442	0.0361	0.0307	0.0234
Colorado	0.0024	0.7957	0.1186	0.0952	0.1045
Connecticut	0.0213	1.2943	0.1644	0.1081	0.1740
Delaware	0.0000	6.0119	0.6001	0.2500	0.9833
Florida	0.0083	6.1262	0.4073	0.2511	0.6580
Georgia	0.9800	0.4262	0.1110	0.0861	0.0809
Idaho	0.0222	4.6268	0.4528	0.2987	0.6056
Illinois	0.0030	0.1041	0.0249	0.0219	0.0147
Indiana	0.0086	0.8264	0.0695	0.0524	0.0814
Iowa	0.0018	0.1288	0.0420	0.0365	0.0235
Kansas	0.0011	0.3356	0.0529	0.0406	0.0484
Kentucky	0.0021	0.4091	0.0591	0.0441	0.0574
Louisiana	0.0002	0.8301	0.0906	0.0547	0.1210
Maine	0.0261	0.8519	0.2238	0.1880	0.1406
Maryland	0.0146	0.8510	0.1440	0.1033	0.1263
Massachusetts	0.0098	0.2119	0.0519	0.0476	0.0287
Michigan	0.0022	0.0667	0.0208	0.0173	0.0131
Minnesota	0.0034	0.9342	0.0657	0.0477	0.0899
Mississippi	0.0007	0.6841	0.1205	0.0859	0.1138
Missouri	0.0070	0.3557	0.0467	0.0335	0.0417
Montana	0.0196	2.0280	0.2420	0.1683	0.2799
Nebraska	0.0010	0.7308	0.0896	0.0507	0.1167
Nevada	0.0000	7.6465	1.0487	0.5834	1.4628
New Hampshire	0.0103	2.1148	0.2014	0.1445	0.2317
New Jersey	0.0047	0.1606	0.0531	0.0469	0.0297
New Mexico	0.0000	4.4771	0.2388	0.1308	0.4656
New York	0.0040	0.1162	0.0297	0.0228	0.0207
North Carolina	0.0013	0.5893	0.0828	0.0605	0.0818
North Dakota	0.0000	1.1902	0.1855	0.1471	0.1756
Ohio	0.0037	0.1276	0.0271	0.0234	0.0178
Oklahoma	0.0005	0.5925	0.0855	0.0637	0.0786
Oregon	0.0299	2.2798	0.3560	0.2550	0.3526
Pennsylvania	0.0034	0.0630	0.0191	0.0156	0.0112
Rhode Island	0.0054	1.0886	0.1977	0.1277	0.1934
South Carolina	0.0000	0.8319	0.1412	0.1065	0.1289
South Dakota	0.0000	0.7101	0.1379	0.1099	0.1303
Tennessee	0.0063	1.1205	0.1054	0.0735	0.1311
Texas	0.0025	0.1174	0.0261	0.0207	0.0189
Utah	0.0195	2.0090	0.3449	0.2296	0.3633
Vermont	0.0036	8.4315	0.3697	0.2119	0.8001
Virginia	0.0074	1.8140	0.1162	0.0715	0.1743
Washington	0.0170	0.9345	0.1879	0.1422	0.1551
West Virgina	0.0044	0.4927	0.1045	0.0823	0.0890
Wisconsin	0.0018	0.1784	0.0448	0.0373	0.0290
Wyoming	0.0000	2.3847	0.3547	0.2199	0.4288

Table II)
Summary Statistics:
Bank Failures as a Percent of Total State Deposits
Quarterly Data by State from 1900Q1 through 1931Q2

State	Minimum	Maximum	Mean	Median	Std Dev
Alabama	0.0000	2.3754	0.1497	0.0000	0.3629
Arizona	0.0000	7.3305	0.2726	0.0000	1.0322
Arkansas	0.0000	27.2548	0.4875	0.0065	2.4735
California	0.0000	1.3374	0.0206	0.0000	0.1225
Colorado	0.0000	5.1208	0.1526	0.0000	0.5147
Connecticut	0.0000	1.0976	0.0240	0.0000	0.1235
Delaware	0.0000	1.8150	0.0183	0.0000	0.1645
Florida	0.0000	17.2992	0.6139	0.0000	2.1472
Georgia	0.0000	4.8684	0.3363	0.0140	0.8475
Idaho	0.0000	15.0950	0.3964	0.0000	1.5196
Illinois	0.0000	2.2249	0.0601	0.0056	0.2168
Indiana	0.0000	3.2982	0.1182	0.0000	0.4210
Iowa	0.0000	2.7875	0.1743	0.0147	0.3875
Kansas	0.0000	1.3150	0.1108	0.0000	0.2210
Kentucky	0.0000	23.1206	0.2542	0.0000	2.0620
Louisiana	0.0000	1.2802	0.0369	0.0000	0.1452
Maine	0.0000	0.9597	0.0274	0.0000	0.1384
Maryland	0.0000	3.9878	0.0799	0.0000	0.3864
Massachusetts	0.0000	1.0100	0.0254	0.0000	0.1120
Michigan	0.0000	1.7823	0.0320	0.0000	0.1672
Minnesota	0.0000	1.2078	0.1055	0.0142	0.2086
Mississippi	0.0000	12.9553	0.2803	0.0000	1.2904
Missouri	0.0000	4.0978	0.0858	0.0086	0.3752
Montana	0.0000	16.9555	0.5315	0.0000	2.0244
Nebraska	0.0000	4.3535	0.2009	0.0000	0.5683
Nevada	0.0000	16.4122	0.3438	0.0000	1.9537
New Hampshire	0.0000	4.1056	0.0362	0.0000	0.3677
New Jersey	0.0000	0.4223	0.0125	0.0000	0.0521
New Mexico	0.0000	41.1642	0.6508	0.0000	3.9088
New York	0.0000	2.6292	0.0777	0.0006	0.3015
North Carolina	0.0000	15.1496	0.2380	0.0000	1.3566
North Dakota	0.0000	18.1556	0.4913	0.0000	1.8636
Ohio	0.0000	0.9244	0.0622	0.0058	0.1438
Oklahoma	0.0000	4.4752	0.1812	0.0000	0.5160
Oregon	0.0000	9.5142	0.1859	0.0000	0.9125
Pennsylvania	0.0000	0.9298	0.0460	0.0009	0.1232
Rhode Island	0.0000	14.8445	0.1230	0.0000	1.3224
South Carolina	0.0000	2.4354	0.2323	0.0000	0.4590
South Dakota	0.0000	12.1289	0.5781	0.0000	1.6025
Tennessee	0.0000	11.4684	0.2215	0.0000	1.0614
Texas	0.0000	3.0744	0.1372	0.0096	0.3596
Utah	0.0000	0.8978	0.0587	0.0000	0.1694
Vermont	0.0000	0.3815	0.0041	0.0000	0.0356
Virginia	0.0000	0.6192	0.0342	0.0000	0.1067
Washington	0.0000	3.6106	0.1210	0.0000	0.4038
West Virgina	0.0000	2.7612	0.0741	0.0000	0.2939
Wisconsin	0.0000	0.6727	0.0398	0.0000	0.1061
Wyoming	0.0000	11.8573	0.2342	0.0000	1.1455

Table III
F Test for Granger Causality:
Aggregate U.S. and State Level from 1900Q1 through 1931Q2

State	Bank to Commercial Failures		Commercial to Bank Failures	
	Test Statistic	P-Value	Test Statistic	P-Value
United States	8.85	0.000	0.88	0.479
Alabama	0.12	0.976	0.29	0.884
Arizona	1.28	0.284	2.27	0.066
Arkansas	2.35	0.058	1.19	0.321
California	31.6	0.000	0.66	0.619
Colorado	0.96	0.431	0.45	0.770
Connecticut	2.04	0.094	0.88	0.478
Delaware	131.20	0.000	0.37	0.827
Florida	0.83	0.510	1.12	0.349
Georgia	0.30	0.880	1.07	0.373
Idaho	1.72	0.151	0.75	0.560
Illinois	3.04	0.020	0.64	0.637
Indiana	7.56	0.000	0.51	0.731
Iowa	0.55	0.699	0.54	0.704
Kansas	0.63	0.645	0.89	0.470
Kentucky	2.26	0.067	0.33	0.857
Louisiana	0.90	0.468	1.08	0.369
Maine	1.63	0.171	0.77	0.548
Maryland	167.87	0.000	0.37	0.827
Massachusetts	2.91	0.025	1.12	0.351
Michigan	5.36	0.001	0.48	0.751
Minnesota	1.39	0.242	0.55	0.697
Mississippi	1.75	0.145	0.52	0.720
Missouri	2.75	0.031	0.43	0.788
Montana	0.68	0.611	1.61	0.176
Nebraska	4.13	0.004	0.62	0.647
Nevada	1.70	0.156	0.44	0.781
New Hampshire	152.57	0.000	0.42	0.792
New Jersey	0.48	0.750	0.98	0.420
New Mexico	0.99	0.413	0.75	0.561
New York	2.55	0.043	0.70	0.592
North Carolina	1.94	0.109	0.46	0.764
North Dakota	6.42	0.000	0.32	0.863
Ohio	0.60	0.665	1.20	0.314
Oklahoma	0.69	0.602	1.82	0.130
Oregon	4.29	0.003	0.40	0.808
Pennsylvania	2.40	0.054	1.30	0.275
Rhode Island	59.95	0.000	0.23	0.918
South Carolina	1.46	0.218	1.54	0.196
South Dakota	2.16	0.078	0.60	0.666
Tennessee	1.82	0.130	1.13	0.348
Texas	12.72	0.000	1.65	0.166
Utah	0.98	0.420	2.02	0.096
Vermont	13.78	0.000	0.33	0.860
Virginia	0.74	0.568	0.95	0.440
Washington	0.72	0.583	0.35	0.843
West Virgina	1.31	0.270	1.02	0.402
Wisconsin	2.51	0.046	0.51	0.729
Wyoming	3.29	0.014	0.97	0.426

Notes

Table IV
Sources of the Credit Channel:
logit Regressions With Credit Channel Indicator
as Independent Variable, t Statistics in Parenthesis

Dependent Variable	Independent Variable: Credit Channel Indicator				
Branch Banking	-0.405				
	(0.575)				
Deposit Insurance		-0.359			
		(0.709)			
Agricultural States			-0.342		
			(0.555)		
Bank Deposits				18.591	
				(0.020)	
Net Loans					43.203
					(0.014)
Adjusted R^2	0.005	0.005	0.005	0.158	0.163

Notes

Table V
Forecast-Error Variance Decompositions
For U.S. Bank Failures and Commercial Failures

Forecast Horizon (Quarters)	Percentage due to Bank Failures:		Percentage due to Commercial Failures:	
	Commerical Failures	Bank Failures	Commercial Failures	Bank Failures
1	17.8%	100.0%	82.2%	0.0%
	(9.2%)	(0.0%)	(9.2%)	(0.0%)
2	22.8	100.0	77.8	0.0
	(11.6)	(0.0)	(11.6)	(0.0)
3	22.0	100.0	78.0	0.0
	(11.3)	(0.0)	(11.3)	(0.0)
4	21.5	100.0	78.5	0.0
	(11.1)	(0.0)	(11.1)	(0.0)
8	18.5	100.0	81.5	0.0
	(10.4)	(0.0)	(10.4)	(0.0)
12	18.4	100.0	81.6	0.0
	(10.4)	(0.0)	(10.4)	(0.0)
16	18.4	100.0	81.6	0.0
	(10.4)	(0.0)	(10.4)	(0.0)
24	18.4	100.0	81.6	0.0
	(10.4)	(0.0)	(10.4)	(0.0)
40	18.4	100.0	81.6	0.0
	(10.4)	(0.0)	(10.4)	(0.0)

Standard errors are listed in parenthesis. They are bootstrapped using
1,000 repetitions of the model.

Figure I. Commercial failures normalized by income and bank failures normalized by bank deposits at the aggregate U.S. level, with both series expressed as percents.

Figure II. Impulse response functions of bank failures and commericial failures to one-standard-error innovations to bank failures and commercial failures.